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A journey among top ten emitter country, decomposition of "Kaya Identity"

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A R T I C L E   I N F O

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A B S T R A C T

Climate change likely poses severe and distinct threats to human life but COP21 as the first-ever universal, legally binding climate deal created a momentum for rapid changes and expects top ten emitters admit reducing as first target group. This article attempts to evaluate four driving forces of GHG emissions (Kaya Identity), in period of 40 years (1971–2012) among top ten emitters (2015), responsible for 67% of all GHG emissions. Single and Multiple Linear Regression Models are used and the coefficients or multipliers yield, describe the size of the effect which independent variables (include demographic, economic, fuel type and energy usage of a society) have on emissions and the trend of changes. Based on SLRM in a global outlook, population, energy intensity and GDP_{capita} are the most and carbon intensity is the least influencing factor. MLRM revealed that carbon intensity for China, GDP for the US, Canada and India, energy intensity for Korea and Brazil and finally population in Russia, Japan and Iran are the critical factor leading to more GHG emissions. The results of the evaluation help policymakers to find the most effective and critical criteria for implementation of emission reduction targets with the focus on best options.

1. Introduction

The rate of anthropogenic carbon dioxide emissions have dramatically increased from (close to) zero before Industrial Revolution and exceed to 35890 Mt CO_2 in 2014. The emission scenarios suggested by the Intergovernmental Panel on Climate Change (IPCC) predicts that no action for mitigating climate change, would lead to concentration of 535–983 ppm of CO_2 by 2100 and potentially 1.1–6.4 °C more global warming. In contrast, a significant cut in emissions is necessary to prevent further climate change (IPCC, 2007). The Fifth Assessment Report of the IPCC (AR5) states that "more than half of the observed increase in global average surface temperature from 1951 to 2010 is caused by the anthropogenic increase in GHG concentrations and other anthropogenic forcing together" (IPCC, 2013).

The most accessible and in practice action to combat climate change and its consequences is a rapid reduction in greenhouse gases (GHGs) emission. Climate change is a global challenge that does not respect national borders. Therefore, international negotiations and summits are trying to encourage countries and nations to strength the global response to climate change and join an international emission reduction treaty. The most important aim of a treaty should be to achieve a legally binding and universal agreement on climate, for keeping global warming below 2 °C.

A closer look to historical emissions of developed countries in one side and the position of developing countries, which are placed at the early stages of growth and economic development, on the other side cause that developed nations be considered as responsible of changes and about developing's pointed finger on them to accept emission cut responsibilities. Annex I and developed countries have been started to mitigate CO_2 emissions (based on legally binding targets or voluntary pledges), but beside an increasingly international pressure for emission cut by some developing countries such as China and India is formed (Zhang, 2004).

During the Paris climate conference (COP21) in December 2015 the first ever universal, legally binding global climate deal is adopted by 195 countries and this agreement is due to enter into force in 2020. The essential elements of this agreement and the outcomes of the UN climate conference to drive action forward include (UNEP, 2015):

- Mitigation – reducing emissions fast enough to achieve the temperature goals,
- A transparency system and global stock take – accounting for climate action,
- Adaptation – strengthening ability of countries to deal with climate impacts,
- Loss and damage – strengthening ability to recover from climate impacts,
- Support – including finance, for nations to build clean, resilient futures.

On the way of achieving this targets, developed parties should concentrate on undertaking emission reduction targets and

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developing's must enhance their mitigation efforts, shift the infrastructure of their economy away from dependency on fossil fuels and create development plans ahead of dinosaur fuels consumption. It is noteworthy that economic aspect of emission cuts is the most important obstacle of countries to follow emission reduction targets. Not only developing countries, but also industrialized need large economic investments to replace dirty fossil fuels with clean, renewable or less-carbon types.

Application of flexible mechanisms such as Clean Development Mechanisms (CDM), Joint Implementation (JI), Emission Trading Scheme (ETS), Carbon Market and the others are proposed approaches to mitigate emissions with least cost. Of course, calculation of potential emission reduction, carbon leakage, carbon price and market deflation and other difficulties changed these solutions to a "less-traveled road". It could be suggested to countries as a way to determine the critical sectors which interfere in emission trends, the contribution of each section and evaluate economic-environmental aspects of emission reduction at national scale.

In light of this conclusion, this article attempts to evaluate which factors must be considered, if any, should be changed to mitigate emissions in most effective way. There are many factors which interfere in the process of GHG emissions but four main driving forces suggested by Yoichi Kaya forms the core of this research.

These factors cover economic, demographic and environmental facet of emissions in a society. In addition, top ten emitter countries of 2015 which are responsible for more than 67% of emissions are evaluated in a period of 40 years (1971–2012) from this point of view. With this introduction, the structure of this article is as follows:

Section 2 review the literatures related to driving forces of GHGs emission and decomposition analysis. In addition, introduced Kaya Identity, methods applied for analysis and data sources. Section 3 reports the empirical results, models estimates and discusses them in detail. Section 4 concludes the paper with some recommendations for future researches.

2. Analytical framework and methods

The emission of GHGs can be classified in five main sector which include Energy, Industrial Processes and Product Use (IPPU), Agriculture, Forestry and Other Land Use (AFOLU) and Waste (IPCC, 2006). Combustion of fossil fuels, with an upward trend, lead to over three quarters of the anthropogenic emissions for Annex I countries and about 60% of global ones. The largest producers of CO_2 emissions worldwide in 2015, based on their share of global CO_2 emissions include China (28.03%), United States (15.9%), India (5.81%), Russian Federation (4.79%), Japan (3.84%), Germany (2.23%), Korea (1.78%), Canada (1.67%), Iran (1.63%) and Brazil (1.41%), respectively (Statista, 2016; Germanwatch, 2015). The rapid growth of population, economic development, welfare improvement by developing countries and in some cases lack of clean and efficient technologies led to increase of fossil fuel consumption and more climate change. However, the rate of change in CO_2 emissions from fossil fuel combustion is completely different among countries. For example, China (114.6-fold), United States (2.1-fold), India (311.2-fold), Japan (11.6-fold), Korea (269.7-fold), Canada (3.1-fold), Iran (108.6-fold) and Brazil (22.3-fold) during a period of 61 years (1950–2011) and for Russian Federation (1.2-fold) and Germany (0.9-fold), during 11 years (2000–2011) have been experienced different trends. The slop of this change is positive and severe for developing and gentler (or sometimes declining) for developed countries.

During recent decades, a distinct body of researches formed to investigate driving forces and analytical tools to unpack the trend of emissions at regional or global scale, especially at this sector (Dai, Zhang, & Huang, 2016; Feng, Davis, Sun, & Hubacek, 2015; Guan, Peters, Weber, & Hubacek, 2009; Karmellos, Kopidou, & Diakoulaki, 2016; Li, Liu, & Li, 2015; Raupach et al., 2007; Song & Zhang 2017; Wang, Chen, & Zou, 2005; Wang, Li, & Zhang, 2017; Wang, Zhu, & Geng, 2013; Wu, Kaneko, & Matsuoka, 2005; York, Rosa, & Dietz, 2003; Ze-yuan & Jiang, 2006; Zhang, Mu, Ning, & Song, 2009). The mathematical models such as Kaya identity, Data Envelope Analysis (DEA), Logarithmic Mean Weight Divisia (LMD), Perfect Decomposition Method and the other models are used to determine the effect of most important-effective driving forces which are mainly population, economic activity, energy efficiency and energy structure.

Among many factors considered as driving forces of CO_2 emissions, these four criteria assigned a great part of researches to themselves. In 1989 and during a seminar organized by IPCC, a Japanese professor named Yoichi Kaya introduced a simple but extensively applicable model to conduct quantitative analysis on CO_2 emissions (Kaya & Yokobori, 1997). This model entitled "Kaya Identity" established a simple mathematical equation which relates economic, demographic and environmental factors to estimate CO_2 emission of human activities as Eq. (1).

$$E_{carbon} = Population \times \frac{GDP}{Person} \times \frac{Energy}{GDP} \times \frac{CO_2}{Energy} \quad (1)$$

Where E_{carbon} is carbon emission rate (GtC/yr); GPD/Person is per capita of gross domestic product ($/person-yr); Energy/GPD is energy intensity, primary energy per unit of GDP (EJ/$) and finally Carbon/Energy is carbon intensity, carbon emissions per unit of primary energy (GtC/EJ).

2.1. Driving forces of GHG emission

2.1.1. Population

The effect of population on emissions is undeniable. There is an increasing concern that growth in demographic statistics lead to rapid increase of energy demand for providing essential requirements, more fossil fuel consumption and so global carbon dioxide emissions. Many researchers focused on this factor and most of these studies have assumed a unitary elasticity of emissions with respect to population changes. It means that doubling in population results in a doubling in emissions (Dietz & Rosa, 1997). However, another research (Shi, 2003) examined this concern among 93 countries for a period of two decades. It revealed that the effect of population on emission growth is heterogeneous across countries with different per capita income levels. The elasticity of emissions with respect to population change is nearly 2 for low- middle income and less than unity among high income countries. The impact of population on CO_2 emissions among European Union countries is the subject of another article and it was shown that for old EU members the elasticity is lower than unity and for recent accession countries this rate is more than proportional (Martínez-Zarzoso, Bengochea Morancho, & Morales Lage, 2007). The relationship between a city size and CO_2 emissions would be a good estimate on the pressure of population on emissions. This question is answered by a research (Fragkias, Lobo, Strumsky, & Seto, 2013) done for United States metropolitan areas (1999–2008) and found that emissions scale proportionally with urban population size but, there is not a direct relationship between scale of a city with emission efficiency. Evaluation of household carbon footprints (HCF) in United States (Jones & Kammen, 2014) discovered that for urban core cities HCF is lower ($\sim$40 t-CO_{2eq}) and for outlying suburbs this rate is higher ($\sim$50 tCO_{2e}). In addition, a weak but positive correlation exits between population density and HCF (before achieving density threshold). Of course, projection of further emissions only based on demographic change is not enough and the other demographic factors such as population growth or decline, ageing, urbanization, and household size are suggested (O'Neill et al., 2012).

At the beginning of Industrial Revolution, in 1750, the world population was about 791 million and today it is more than 7.442 billion. Carbon dioxide concentration, as a good indicator of how much fossil fuel is burned, has increased from a preindustrial value of

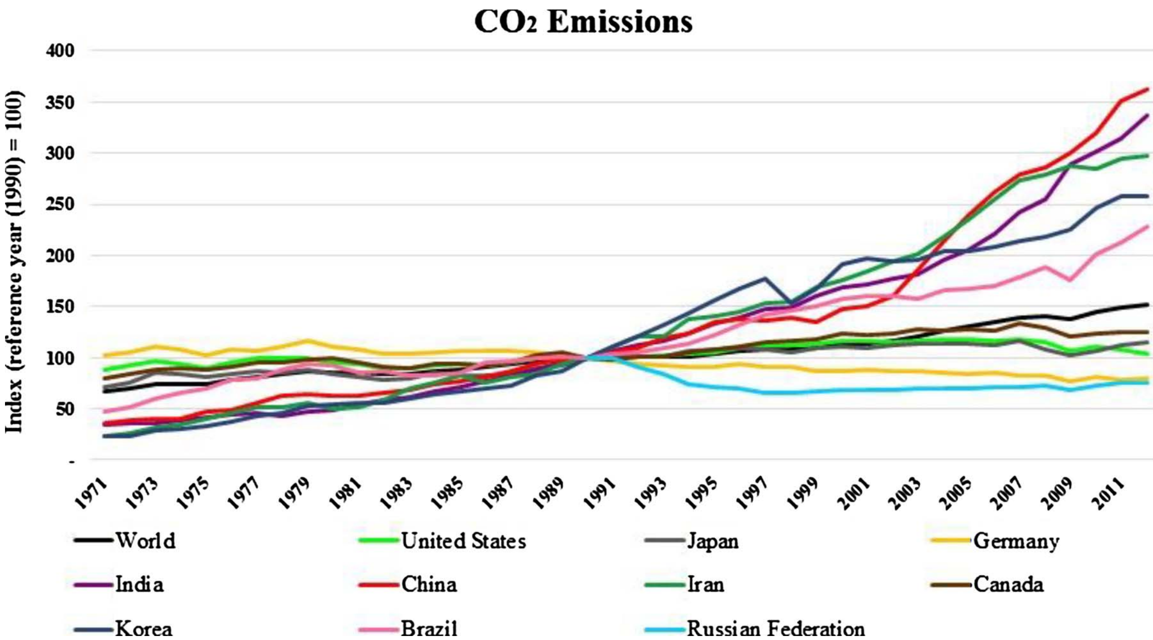

Fig. 1. CO_2 emission pattern among top ten emitters.

280 ppm–403.38 ppm in September 2017 (NOAA, 2017). Of course, different slopes and patterns can be fitted out for different periods (Raupach et al., 2007).

In 2015, top ten emitter countries include about 50.94% of world's population and 67.09% of GHGs emissions (UN, 2016). Figs. 1 and 2 paid to pattern of emission and population growth during four decades among top ten emitters, respectively. It is noteworthy that each country is compared with itself during long time and year 1990 is selected as the reference year in this evaluation. These statistics confirm that a positive relationship between population and emission is predictable.

It should be mentioned that per capita of emissions is not equal around the world and comparison of well-being, poverty and technology level made this achievement completely expected. For example, Qatar (11.97), Trinidad & Tobago (10.14), Kuwait (7.94), Brunei-Darussalam (6.54) and Oman (5.85) experienced the largest and Democratic Republic of the Congo (0.01), Chad (0.01), Burundi (0.01), Rwanda (0.02) and Somalia (0.02) the lowest rate of CO_2 emissions per capita (metric tons of carbon) in 2011 (CDIAC, 2016). China as the world's biggest greenhouse gas emitter has the per capita of 7.1 tCO_2/person and ranked as 51th (in 2014). The other big emitter countries have different per capita (tCO_2/person) and ranking so that United Stated 17 (11th), India 2.0 (130th), Russian Federation 11.0 (25th), Japan 9.7 (33th), Germany 9.8 (32th), Korea 12 (22th), Canada 16 (16th), Iran 7.9 (43th) and finally Brazil 2.5 (119th) (GCP, 2015).

Fig. 3 shows the position of top ten emitters in population and emission based of their global share. Brazil and India, despite their high population, have a small share in emissions. China and United States experience high levels, both in population and emissions. For example, United States having only 4.44% of world population, dedicated 15.9% of global emissions.

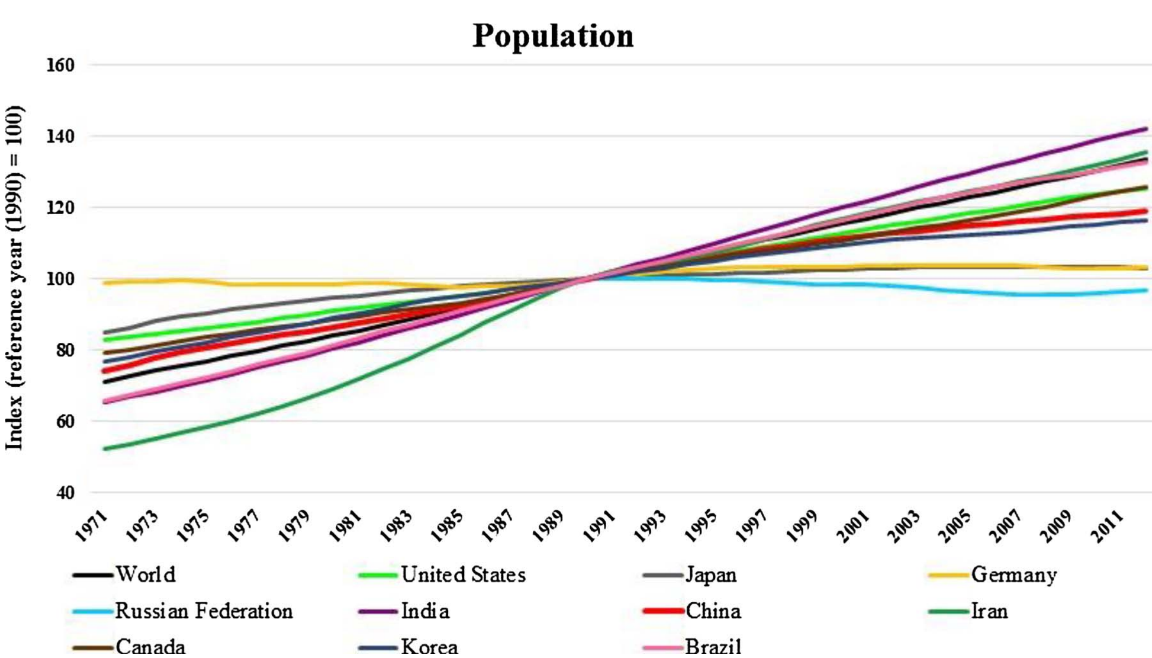

Fig. 2. Population growth among top ten emitters.

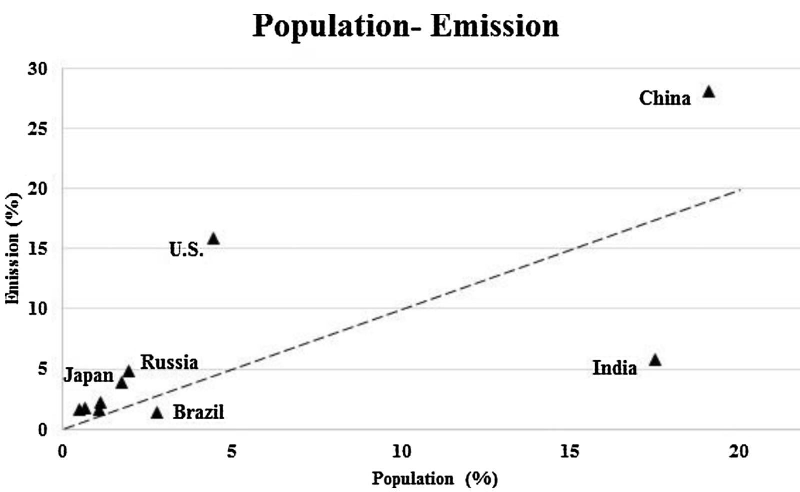

Fig. 3. Global population- emission share among top ten emitters.

Based on finding of a new Oxfam entitled "Extreme Carbon Inequality", released during climate talks in Paris, "Climate change is inextricably linked to economic inequality". During this paper, emissions from individual consumption rather than national production is estimated. This part of emissions makes up 64% of global emissions. The average footprint of individual consumption emissions among the richest 1% of people is 175 times that of the poorest 10%. Around 50% of emissions attributed to the richest 10% of people around the world with a carbon footprint 11 times as high as the poorest half of the population and 60 times as high as the poorest 10%. The poorest half of the global population (around 3.5 billion people) are responsible for only around 10% of total global emissions (Oxfam, 2015). Despite this inequality, economic situation and in a better word, Gross Domestic Product (GDP) can encourage carbon emissions and is considered as the second important driving force of GHG emissions.

2.1.2. Economy

Economy is the other factor which influence on emission trends. Among many factors which introduced in this relation, per capita of GDP is the best description for this purpose. Per capita of GDP is a measurement of the total economic output of a country divided by its population and a general index for evaluation of welfare level. Application of the STIRPAT model for evaluation of CO_2 emissions among countries with different income levels over the period 1975–2000, shows that economic growth has the greatest impact on emissions and the impact of GDP per capita on the total CO_2 emissions is very great among low income countries (Fan, Liu, Wu, & Wei, 2006). Analyses of CO_2 emissions in the United States show that economic growth before 2007 and its recession after this date played a comparatively important role in emissions (Feng et al., 2015). In another research, the largest positive effect on emission changes among all the major economic sectors of China over 1991–2006 had been linked to economic activity (Zhang et al., 2009) and contribution rate of economic growth to per capita of emissions is estimated by an exponential growth (Ze-yuan & Jiang, 2006).

Countries follow different economic structures during their development path. The first block of this structure entitled "Primary" involves the retrieval and production of raw materials. The second block "Secondary" include the transformation of raw or intermediate materials into goods. Supplying of services to consumers and businesses is the third step of development, "Tertiary". The economic structure of a country may include all sectors but with variable portions. The rate of economic gain and environmental load of each sector is different from the others and many theories and models try to interpret this pattern. For example, the Environmental Kuznets Curve (EKC) suggests an inverted U relationship between economic growth (including structural changes) and environmental pollution (Agras & Chapman, 1999; Fodha & Zaghdoud, 2010; Stern, 2004; Sun, 1999). Many studies paid to the relationship between the transition of economic sectors and environmental consequences (Guan et al., 2009; Nansai et al., 2009; Okamoto, 2013; Suh, 2006). Developed countries started this path from industrial revolution and during time passage have learned how to make money with the least environmental damage but, developing and less developed are at the early stages of this transition.

From economical perspective, in the form of GDP per capita (2014), China with 3863 constant 2005 US$ ranked as 94th, United Stated 46405 (9th), India 1234 (130th), Russian Federation 6844 (65th), Japan 37595 (20th), Germany 39852 (14th), Korea 24566 (29th), Canada 38255 (16th), Iran 3541 (97th) and Brazil 5881 (72th) are the other countries in this unequal battle (World Bank, 2016a). Figs. 4 and 5 depict a wide gap among top ten emitters from this perspective and the trend of GDP per capita of top ten emitters during time passage.

2.1.3. Energy intensity

The third parameter which made this concept more quantified is "Energy Intensity". Energy intensity as a measure of energy efficiency, evaluate the amount of energy used to produce a dollar worth of economic output, or conversely the amount of economic output that can be generated by one standardized unit of energy. Many lines of statistic evidence show that in the year 1980, world was at the most efficient situation in achieving the highest economic growth and least carbon emissions for a given level of energy consumption for that year. The efficiency index faced with reduction and then a declining trend in the next 8, 7 years, respectively and finally growth from 1996 toward 2001 (Ramanathan, 2006). Different studies confirm that considerable decrease in CO_2 emissions in China is mainly due to the improved energy intensity (Wang et al., 2005; Zhang et al., 2009). In addition, it is proved that the effect of energy intensity is more critical among upper-middle income countries (York et al., 2003).

The stage of industrialization, mixture of services and manufacturing in economic structure of a country, improvements in energy efficiency and level of technology used in a country are some factors influence on energy intensity. In 2014, Colombia (0.065), United Kingdom (0.082), Spain (0.093), Italy (0.093) and Egypt (0.097) have the lowest and Russia (0.034), Uzbekistan (0.333), Ukraine (0.320), South Africa (0.252) and Iran (0.225) have the highest energy intensity (koe/$2005p[1]) around the world (Enerdata, 2016). Climate circumstances and welfare level are two factors which can influence on energy intensity of a country regardless of efficiency. Fig. 6 paid to energy intensity of top ten emitters from past to date.

[1] koe/$2005p: kilogram of oil equivalent/US$ exchange, price and purchasing power in 2005.

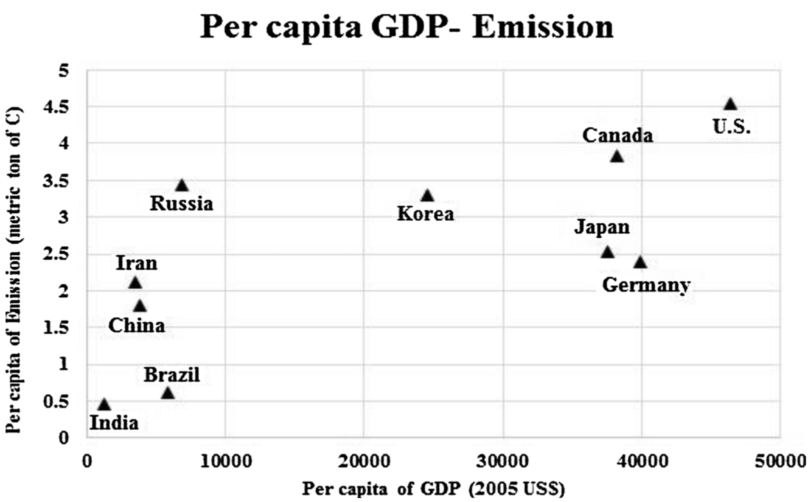

Fig. 4. GDP_{capita}- emission among top ten emitters.

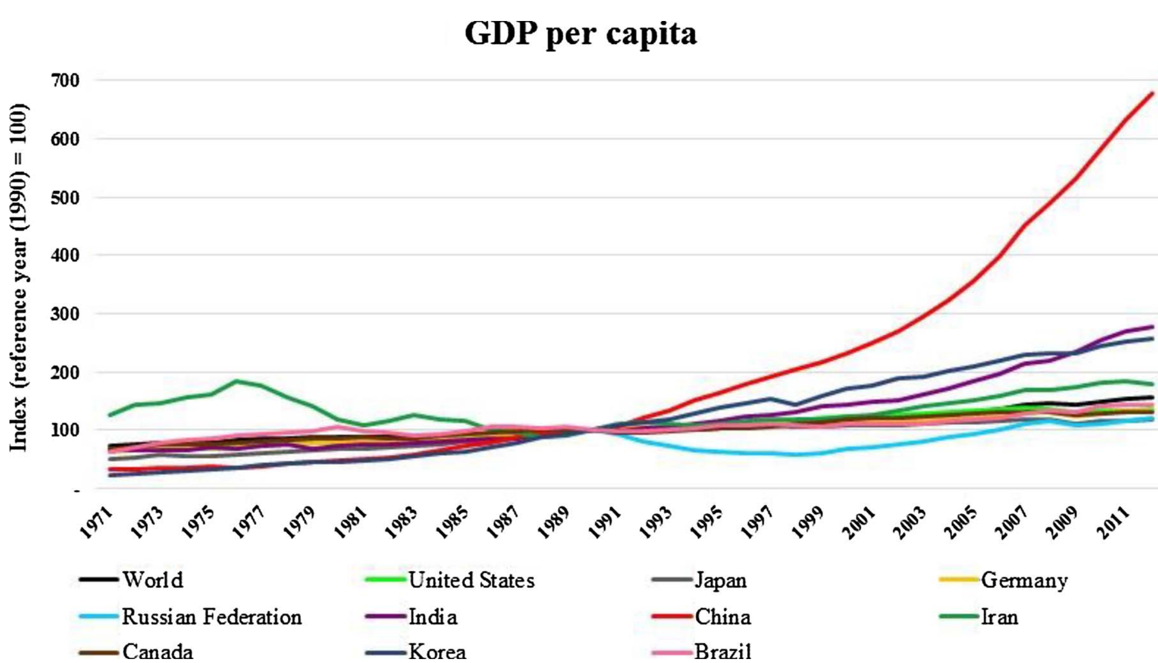

Fig. 5. Per capita of GDP among top ten emitters.

2.1.4. Carbon intensity

The worldwide economic growth in combine with increase in energy demand play a key role in increase of emissions. Global total primary energy supply (TPES) increased by almost 1.5 folds along 1971–2013. Of course, due to diverse national structures this percentage varies greatly by country.

Based on availability, economy and environmental regulations, countries select different sources of energy. Coal represented about 29% of world TPES in 2013 and because of its heavy carbon content per unit of energy released, close to 46% of the global CO_2 emissions are coal sourced. Many Countries are dependent to coal sources for electricity generation. For example, China (75%), United States (39.9%), India (72.8%), South Africa (93.7%) and Kazakhstan (81.3%) are some of them.

Electricity production by oil is rare but countries such as Benin, South Sudan, Senegal, Malta, Lebanon, Eritrea and Curacao generate completely oil based electricity (World Bank, 2016b). In a global outlook, from the late 1980s until the early 2000s, approximately 40% of CO_2 emissions are based on coal burning and the same amount for oil (IEA, 2015). The rate of carbon emissions per unit of energy or fuels consumed is considered as carbon intensity.

Among world countries, Nigeria (0.054), Norway (0.057), Sweden (0.101), Colombia (0.141) and France (0.151) have the lowest and Uzbekistan (0.762), Russia (0.724), Ukraine (0.699), South Africa (0.673) and Kazakhstan (0.645) experience the biggest rate of carbon intensity (kCO_2/\$2005p) (Enerdata, 2015). The pattern of carbon intensity improvement among top ten emitters is shown in Fig. 7. In two ways carbon intensity can reduced. The first is a change in the composition of energy resources which consumed and the second is a decline in energy intensity. For example, coal is much more carbon intensive than natural gas (nearly twice), so shift to another fuel such as gas would lead to a reduction in carbon intensity. Application of more reliance and low carbon energy sources like solar, hydro, geothermal, nuclear and so on can provide even greater benefits (Xiaowei & Gallagher, 2014). The statistics related to driving forces of top ten emitters is presented in Table 1.

Introduction and analyses of these four factors have been done among top ten emitter country of 2015 (China, United States, India, Russian Federation, Japan, Germany, Korea, Canada, Iran and Brazil) to determine the role of each factor and pattern of changes during a long period (1971–2012). By this approach, the importance and the degree of influence for each factor would be realized and as a consequence

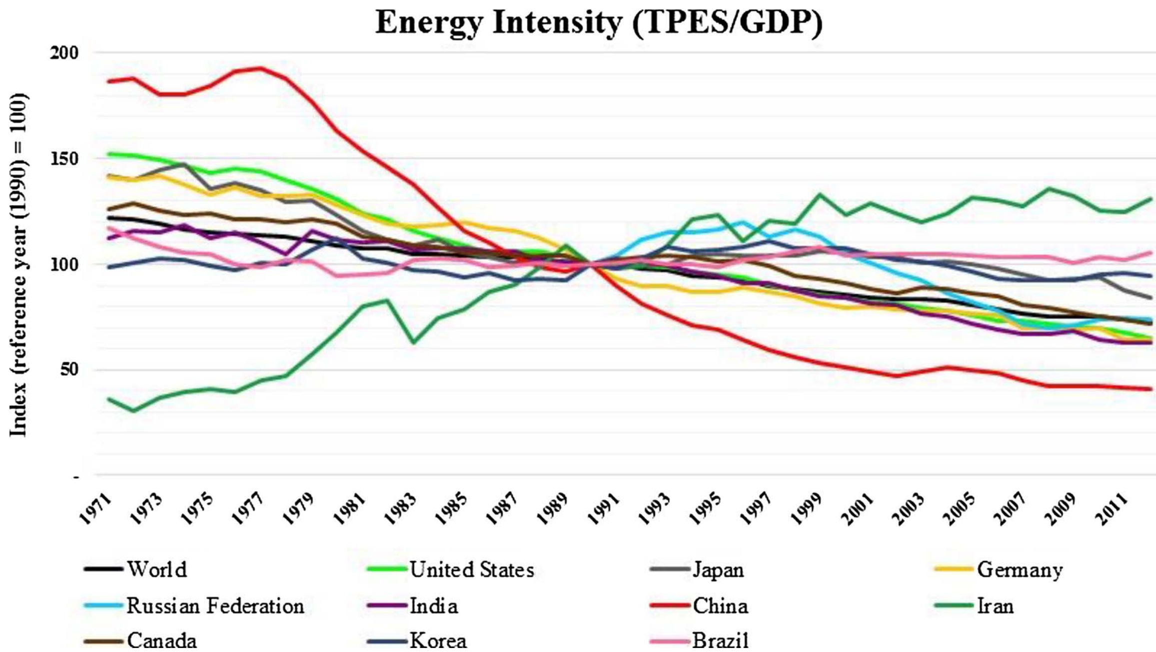

Fig. 6. Energy Intensity among top ten emitters.

better decision on the way of mitigation efforts would be shaped.

2.2. Model description and statistical analysis

The next step of evaluation paid to effect of each driving force on emissions at target country during time interval. It means that among different factors, the role and share of each factor be identified. To answer this question, regression analysis could be suggested. Regression analysis as a statistical method attempts to model the relationship between two or more explanatory variables and a response variable by fitting a function to observed data. In linear regression methods, the function is a linear (straight-line) equation. For Simple Linear Regression Model (SLRM), a single independent variable is used to predict the value of a dependent variable but Multiple Linear Regression Model (MLRM) used two or more independent variables to predict the value of a dependent variable. The difference between the two is the number of independent variables while in both cases there is only one dependent variable. Eq. (2) is a suggested formula as MLRM for this research. SLRM is similar with this difference that just one independent and one dependent variable interfere. The coefficients or multipliers yield, describe the size of the effect the independent variables have on emission amounts and the sign on the coefficient (positive or negative) shows the direction of effect, increase or decrease, respectively. Regression coefficients represent the mean change in the response variable for one unit of change in the predictor variable while holding other predictors in the model constant. It should be mentioned that nature is rarely (if ever) perfectly predictable, and usually there is substantial variation of the observed points around the fitted regression line. The deviation of a particular point from the regression line is called the residual value. When the variability of the residual values

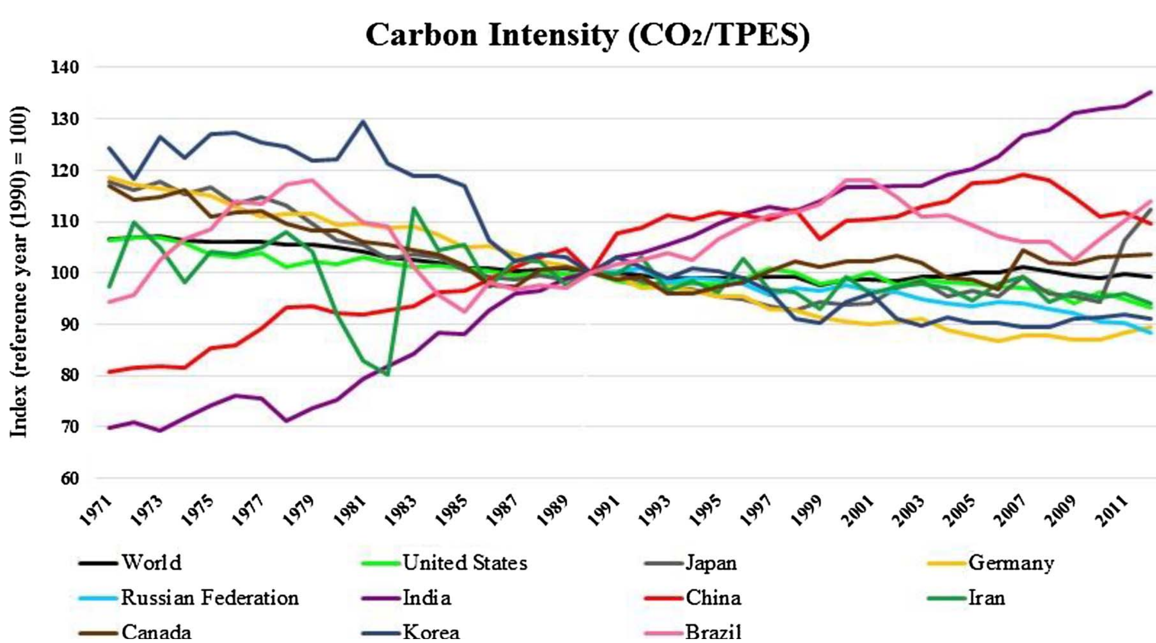

Fig. 7. Carbon Intensity among top ten emitters.

Table 1
Driving forces of CO_2 emissions among top ten emitters.

Rank	Country	Population (%)	CO_2 emission (%)	GDP (per capita) 2005 US $	Energy Intensity koe/2005 US $	Carbon Intensity kCO_2/2005 US $
1	China	19.13	28.03	3863	0.206	0.545
2	United States	4.44	15.9	46405	0.150	0.355
3	India	17.51	5.81	1234	0.133	0.356
4	Russian Fed.	1.94	4.79	6844	0.329	0.724
5	Japan	1.76	3.84	37595	0.109	0.279
6	Germany	1.13	2.23	39852	0.101	0.246
7	Korea	0.68	1.78	24566	0.172	0.375
8	Canada	0.49	1.67	38255	0.190	0.399
9	Iran	1.09	1.63	3541	0.220	0.539
10	Brazil	2.78	1.41	5881	0.117	0.190

around the regression line relative to the overall variability is small, the predictions from the regression equation are good. The Coefficient of determination or R-Square is a statistical indicator to evaluate how well the model fits the data. Another indicator should be aware is the P-value of regression. As an illustrative exercise, independent variables may be correlated, a condition known as multicollinearity, the coefficients on individual variables may be insignificant when the regression as a whole is significant. P-value for each term tests the null hypothesis about correlation of each individual variable with the dependent variable. A low p-value (< 0.05) is likely and mentioned that changes in the predictor's value are related to changes in the response variable. Conversely, a larger (insignificant) p-value suggests that changes in the predictor are not associated with changes in the response. Based on the purpose of this study, two forms of regression (include SLRM and MLRM) are fitted based on data availability (1971–2012) among all target countries, individually, and related coefficients are determined. Four driving factors (include population, per capita of GDP, energy and carbon intensity) are considered as independent variables (Table 1). The softwares such as Excel and MatLab are used for statistical analysis.

$$Y_i = F(x_i) = \beta_0 + \beta_1 . X_{1i\,j} + \beta_2 . X_{2i\,j} + \beta_3 . X_{3ij} + \beta_4 . X_{4i\,j} + \varepsilon_i \tag{2}$$

Where X_{1i} is population; X_{2i} is per capita of GDP; X_{3i} is energy intensity; X_{4i} is carbon intensity; β_n are coefficients of each driving force; ε_i model deviations, i is target country and j include time interval.

The Eq. (2) is used to estimate parameters for all target countries by means of Multiple Linear Regression Model (MLRM) and results presented in Table 2. In this analysis, all four driving factors (include population, per capita of GDP, energy and carbon intensities) are considered simultaneously and based on calculated coefficients, a linear equation in the form of Eq. (2) could be suggested. Table 3, paid to evaluation of a relationship between emissions and driving forces, but individually (SLRM). It means that once carbon dioxide emissions with population are considered and the best linear equation between them is suggested and this process is repeated for the other three variables. The coefficient of determination, denoted R^2 is a statistical measure of how close the data are to the fitted regression line.

2.3. Data reference and processing

To achieve the goal of this work, five types of information include population, GDP, energy intensity, carbon intensity and CO_2 emissions from fossil fuels, related to top ten emitter countries, are needed. Population census are collected from World Population Prospects- the 2015 revision (UN, 2016). Information related to economic output of countries, such as GDP (constant 2005 US$) and carbon intensity received from the World Bank-World Development Indicators website. Besides, energy intensity information is calculated based on data provided by U.S. Energy Information Administration (EIA). During this study, CO_2 emissions from fossil-fuel burning are received from Carbon Dioxide Information Analysis Center (CDIAC), World Bank Data Center and for some cases, these emissions are estimated from fuel consumption data of each country and IPCC 2006 guideline is used for calculation of emissions.

3. Results and discussion

Climate change and its consequences poses a fundamental threat to the places, species and people's livelihoods. Therefore, rapid reduction in emission of GHGs should be placed as a priority of international actions. Identification of the most important driving forces, effective on emissions can shorten the path of mitigation efforts. Among many driving forces suggested for this purpose, population, per capita of GDP, energy intensity and carbon intensity are selected as proposed criteria by Kaya identity. For this evaluation, top ten emitter countries of 2015 which are responsible for 67% of GHG emissions and data related to a long period (1971–2012) are considered. The regression analysis is used to produce an equation that will predict a dependent variable (CO_2 emissions) using one or more independent variables (driving forces of emissions). The coefficients or multipliers yield, describe the size of the effect the independent variables have on emissions and the sign on the coefficient (positive or negative) shows the direction of effect, increase or decrease, respectively. Two forms of single and multiple linear regression (SLR & MLR) are analyzed in this research. Tables 2 and 3 represent the results of the multiple linear regression model and single linear regression model for all top ten emitters, respectively. Regression coefficients represent the mean change in the response variable for one unit of change in the predictor variable while holding other predictors constant in the model.

3.1. Global evaluation of effective factors on GHG emissions

Global evaluation of single independent variables show that population and GDP have increasing and energy intensity and carbon intensity decreasing effects on emissions. Population is the most influencing factor and energy intensity and GDP_{capita} are placed at the next stages. The effect of carbon intensity in compare with the other parameters is less considerable.

Multiple linear regression of world data revealed that GDP_{capita}, population and energy intensity are priorities of influence on emissions, respectively. The large amount of p-value (> 0.05) suggests that changes in the predictor of carbon intensity are not associated with changes in the response of emissions.

3.2. National evaluation of effective factors on GHG emissions

Before UN negotiations in Paris (COP21), the countries around the world submitted their pledges to the UN, setting out how far they intend to reduce their greenhouse gas emissions. These promises, known as "Intended Nationally Determined Contributions", or INDCs, used to determine the success of the deal UN was hopeful to reach (December 2015-Paris). The estimates show that, if INDCs fully implemented, the global warming would be in the range of 2.7 °C, a significant progress but still above 2 °C.

China as the largest contributor to carbon emissions pledged to produce 20% of its energy from low-carbon sources by 2030 and to cut emissions per unit of GDP by 60–65% of 2005 levels by 2030. In this path, carbon intensity and GDP_{capita} as significant predictors in multiple regression and carbon intensity and population for individual variable regression are the most effective parameters. During multiple regression, the p-value for population and energy intensity are greater than the common alpha level of 0.05, which indicates that they are not statistically significant.

United States can consider GDP_{capita} and population as the primary

Table 2
The MLRM of CO_2 emissions for world and top ten emitter country.

	Multiple R	R Square	Variables	Coefficients	Standard Error	P-value
World	0.9990	0.9979	Intercept	−138.4591	40.7749	1.65E-03
			X1	0.7904	0.1485	5.20E-06
			X2	0.8280	0.0590	2.21E-16
			X3	0.7377	0.1462	1.22E-05
			X4	0.0201	0.2466	9.36E-01
China	0.9980	0.9960	Intercept	−146.0837	57.0342	1.46E-02
			X1	−0.9852	0.6591	1.43E-01
			X2	0.4894	0.0143	1.31E-29
			X3	0.1858	0.1028	7.88E-02
			X4	2.6015	0.3882	7.09E-08
United States	0.9610	0.9235	Intercept	−16.2680	44.0257	7.14E-01
			X1	−0.9055	0.2885	3.33E-03
			X2	1.1848	0.1554	4.24E-09
			X3	0.2256	0.0826	9.59E-03
			X4	0.6803	0.3773	7.95E-02
India	0.9994	0.9988	Intercept	−228.4524	28.4660	1.28E-09
			X1	0.2869	0.2432	2.46E-01
			X2	1.1760	0.0323	1.44E-30
			X3	0.7907	0.1895	1.75E-04
			X4	1.0590	0.2128	1.51E-05
Russian Federation	0.9846	0.9695	Intercept	−627.3831	105.5726	1.27E-05
			X1	5.1457	1.4398	2.17E-03
			X2	0.6204	0.0897	1.82E-06
			X3	0.0621	0.2024	7.63E-01
			X4	1.4384	0.2639	3.53E-05
Japan	0.9963	0.9926	Intercept	−288.5745	22.5928	3.92E-15
			X1	1.7859	0.1901	2.45E-11
			X2	0.7880	0.0307	3.68E-25
			X3	0.6959	0.0334	4.95E-22
			X4	0.6000	0.0518	7.37E-14
Germany	0.9675	0.9361	Intercept	263.7518	78.1605	1.75E-03
			X1	−1.5321	0.4676	2.29E-03
			X2	0.0003	0.1790	9.99E-01
			X3	0.5552	0.1508	7.37E-04
			X4	−0.6866	0.3048	3.03E-02
Korea	0.9987	0.9974	Intercept	−252.4625	33.8563	7.04E-09
			X1	0.9226	0.2302	2.85E-04
			X2	0.9408	0.0304	4.81E-28
			X3	1.2626	0.1176	6.41E-13
			X4	0.4226	0.1392	4.39E-03
Canada	0.9938	0.9876	Intercept	−230.1801	22.9865	4.42E-12
			X1	0.7466	0.1281	1.07E-06
			X2	1.1442	0.0779	5.20E-17
			X3	1.0709	0.1026	1.40E-12
			X4	0.3330	0.0650	9.62E-06
Iran	0.9926	0.9853	Intercept	−213.7223	43.0428	1.57E-05
			X1	2.9373	0.4978	8.56E-07
			X2	1.0040	0.1028	8.65E-12
			X3	−0.0350	0.4010	9.31E-01
			X4	−0.6945	0.4060	9.55E-02
Brazil	0.9984	0.9968	Intercept	−464.1596	14.8145	3.06E-28
			X1	0.9007	0.0539	7.92E-19
			X2	1.5306	0.0670	2.08E-23
			X3	2.2008	0.1194	3.07E-20
			X4	1.0001	0.0636	5.74E-18

driving forces, with a negative sign for population in MLR and the population and GDP_{capita}, for single variable regression, respectively to achieve 26–28% domestic reduction in GHGs of 2025 compared to 2005. The amount of p-value reject consideration of carbon intensity as an independent variable.

India can consider the priority of important in the form of $GDP_{capita} > CI > EI$ for MLR and $CI > Pop > GDP_{capita} > EI$ in SLR to be successful in its emission reduction targets. The pledges they suggested include 33–35% reduction in emission intensity by 2030, compared to 2005 levels and electricity generation by non-fossil fuels. Increase of carbon sinks in the form of tree cover is another part of Indians' program for emission improvement.

Russian pledge emphasized on "maximum possible account of the land sector" and they needs to reduce 25–30% domestic emissions by 2030 compared to 1990. The driving forces based on influence are as follows: $Pop > CI > GDP_{capita} > EI$, in both single and multiple linear regression. However, EI is considered as a dependent criteria.

Japan suggested to reduce its emissions 26% by 2030 on 2013 level and most concentration is on power generation. This analyses show that $Pop > GDP_{capita} > EI > CI$ can be used as priorities of influence on

Table 3
The SLRM of CO_2 emissions versus driving forces (individually) for world and top ten emitter country.

	Variables	R Square	Equation
World	CO_2-Population	0.9493	Y = 1.1964X − 18.652
	CO_2-GDP_{capita}	0.9925	Y = 0.9905X − 1.5489
	CO_2-Energy Intensity	0.9506	Y = −1.5343X + 252.02
	CO_2-Carbon Intensity	0.5187	Y = −5.7389X + 686.01
China	CO_2-Population	0.7626	Y = 5.7777X − 441.76
	CO_2-GDP_{capita}	0.986	Y = 0.5024X + 38.791
	CO_2-Energy Intensity	0.6389	Y = -1.3311X + 270.18
	CO_2-Carbon Intensity	0.6045	Y = 6.1764X − 498.34
United States	CO_2-Population	0.7281	Y = 0.6232X + 39.02
	CO_2-GDP_{capita}	0.804	Y = 0.3621X + 66.179
	CO_2-Energy Intensity	0.6389	Y = −0.2859X + 133.09
	CO_2-Carbon Intensity	0.411	Y = −1.9284X + 296.17
India	CO_2-Population	0.9133	Y = 3.4463X − 226.64
	CO_2-GDP_{capita}	0.986	Y = 1.3849X − 43.463
	CO_2-Energy Intensity	0.9483	Y = -4.704X + 573.79
	CO_2-Carbon Intensity	0.8952	Y = 3.8712X − 260.8
Russian Federation	CO_2-Population	0.1947	Y = 2.5814X − 178.82
	CO_2-GDP_{capita}	0.0683	Y = 0.1218X + 63.868
	CO_2-Energy Intensity	0.0141	Y = 0.0656X + 68.101
	CO_2-Carbon Intensity	0.2059	Y = 1.344X − 54.26
Japan	CO_2-Population	0.7418	Y = 2.2176X − 121.38
	CO_2-GDP_{capita}	0.874	Y = 0.5597X + 45.981
	CO_2-Energy Intensity	0.5093	Y = −0.5873X + 161.62
	CO_2-Carbon Intensity	0.4438	Y = −1.1478X + 214.49
Germany	CO_2-Population	0.8428	Y = −4.2488X + 525.74
	CO_2-GDP_{capita}	0.86	Y = −0.47X + 143.23
	CO_2-Energy Intensity	0.9036	Y = 0.4094X + 55.018
	CO_2-Carbon Intensity	0.844	Y = 0.9773X − 1.372
Korea	CO_2-Population	0.929	Y = 6.0322X − 478.54
	CO_2-GDP_{capita}	0.9867	Y = 0.9912X + 4.7698
	CO_2-Energy Intensity	0.0089	Y = −1.256X + 250.5
	CO_2-Carbon Intensity	0.8336	Y = −4.8725X + 638.54
Canada	CO_2-Population	0.8919	Y = 1.0437X + 0.547
	CO_2-GDP_{capita}	0.941	Y = 0.7533X + 29.251
	CO_2-Energy Intensity	0.8308	Y = −0.8753X + 195.61
	CO_2-Carbon Intensity	0.2647	Y = −1.3877X + 250.44
Iran	CO_2-Population	0.8844	Y = 3.0779X − 164.5
	CO_2-GDP_{capita}	0.1846	Y = 1.3432X − 46.721
	CO_2-Energy Intensity	0.7408	Y = 2.1798X − 73.718
	CO_2-Carbon Intensity	0.0985	Y = -4.5035X + 578.84
Brazil	CO_2-Population	0.9151	Y = 2.1322X − 94.734
	CO_2-GDP_{capita}	0.8816	Y = 2.5019X − 142.98
	CO_2-Energy Intensity	0.0019	Y = 0.482X + 71.782
	CO_2-Carbon Intensity	0.1647	Y = 2.6439X − 160.76

emissions of this country. However, SLR show a weak relationship between emissions and each driving force.

The effect of population on Germany emissions is negative (both in single and multiple analyses). It means that population growth can lead to emission reductions. Evaluation of p-value says that GDP_{capita} and carbon intensity are insignificant variables for this region. But, after population, energy intensity is the best.

A 37% reduction on BAU emissions by 2030 is the INDC suggested by Korea. Based on MLR, EI > GDP_{capita} > Pop > CI and as SLR, Pop > CI > EI > GDP_{capita} are the order of influencing factors. Both energy intensity and carbon intensity have negative and decreasing effect on emissions.

Canada intend to invest on land sector and forestry and 30% reduction by 2030 based on 2005 level is the aim of this country. SLR suggests Pop > EI > GDP_{capita}, but MLR proposal include GDP_{capita} > EI > Pop > CI.

Based on analyses results in SLR and MLR, respectively, Pop > EI and Pop > GDP_{capita} > CI are the key driving forces of Iran on the way on achieving emission reduction targets. Energy intensity with a p-value more than 0.05 is not an influencing factor. Iran pledges pointed to 4% emission cut by 2030 relative to BAU which in the case of international support of $35bn, this amount could increase to 12%. It should be mentioned that both elements are conditional on the end of sanctions.

Brazil pledge pointed to 37% cut by 2025, with a further indicative target of a 43% by 2030, compared to 2005 levels. It seems that Pop > GDP_{capita} in SLR and EI > GDP_{capita} > CI > Pop for MLR could be the stage of consideration by this country as the most important driving forces of emissions.

Although the results predicted by single multiple regression is different from multiple regression in many cases but, evaluation of both can help for better design making. The increasing effect of population in Russian Federation, Japan and Iran, GDP_{capita} for the world, United States, India and Canada, energy intensity in Germany, Korea and Brazil and finally carbon intensity in China are the most important factors which lead to emission increases. On the other side, population has a serious decreasing effect in China, United States and Germany. It means that population growth could result emission cut. For Iran, carbon intensity is an influencing factor in emission decreases.

Comparison of results from this research with real data (presented in Figs. 1–7) revealed that in the case of CO_2 emissions, Germany and Russian Federation experience a decreasing slope, developed countries such as Canada, United States and Japan an insensible increase and developing ones include China, India, Iran, Korea and Brazil have a rapid increase in emissions. With the exception of Russian Federation, the population has a growing path among all countries but with different rates.

The rapid increase in GDP_{capita} over time is obvious for China. The same pattern repeated for carbon intensity of this country that represent application of dirty, carbon intensive fuels such as coal and lignite in electricity generation and industries. The opposite direction can be seen about energy intensity of this country which is sharply decreasing because of application of strict policies in this relation. Iran follows in increasing after decreasing path about GDP_{capita} and increasing route about energy intensity. The diagram related to carbon intensity is much fluctuated specially about Brazil but rapid increase in India carbon intensity is clear. The other target countries experience a small decrees about energy intensity and small increase in carbon intensity.

3.3. Interpretation of multicollinearity test

In statistics, whenever two or more of the predictors in a regression model are moderately or highly correlated, it could be interpreted as multicollinearity. Variance Inflation Factors (VIF) is a factor can be help to detect multicollinearity and quantifies how much the variance is

inflated. The general rule of thumb is that VIFs exceeding 4 warrant further investigation, while VIFs exceeding 10 are signs of serious multicollinearity requiring correction.

For this research the multicollinearity test is done especially about two independent factors of X_3 and X_4, energy intensity and carbon intensity, respectively. The amount of VIF was completely different from a country to another. The VIF related to energy intensity was high for most of countries except Japan, Korea and Brazil. The same evaluation had done for carbon intensity and results show a multicollinearity in CI for world data, China, India and Germany. To solve this problem two methods are suggested. The first option is to remove one of the two predictors from the model. However, comparison of Kaya Identity results in prediction of CO_2 emissions (by considering all four independent variables) with real data among 215 world countries revealed that about 80% of emissions are estimated accurate (with less than 20% error). It could be a good scientific reason for needing all of the predictors to remain in the model. The second option for solving multicollinearity is to collect new data which is impossible. Because this research is organized based on real data not sampling. It is suggested that future researches concentrate on a new extended or improved Kaya identity with no multicollinearity problem in variables which is far from the object of this article.

4. Conclusions

The cost of emission cut activities is one of the most important obstacles which encourage countries to free ride in the path of mitigation efforts but, identification and evaluation of the most influencing factors which control emissions can help policy makers to select the best and most effective steps of emission reduction. Of course, this research is one of the first steps and the driving forces can interfere on the rate of emissions are not limited to these four criteria but, Kaya identity as a successful and simple model can be used for this evaluation. It is suggested that the other factors and more complicated criteria be examined for this purpose and more complicated models extract for better understanding of countries in the subject of carbon management.

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